LUISS Università Guido Carli

Department of Economics and Finance

Thesis in

IO and Competition Theory

The New Frontier of Pricing

Supervisor | Student

Chiar.mo Prof. | Riccardo Ursino

Gian Luigi Albano

Signature | *Signature*

Academic Year 2018/2019

The new frontier of pricing

Dynamic pricing and its applications

1. What is dynamic pricing and why firms use it 4

1.1. Rational decision-making process 4

1.2. How elasticity affects the success of dynamic pricing 5

2. The industries where it is applied 7

2.1. First application 7

2.2. Development 8

2.3. An unexpected application 9

3. How it works 10

3.1. Historical data 10

3.2. Algorithms 11

4. Industry vs. Customers 14

4.1. Customers' point of view 14

4.2. How customers can exploit it 15

4.3. A microeconomic consideration: extraction of consumer surplus 15

5. Big data and AI 17

5.1. Clients' profiling and the Uber case 17

5.2. Rational decision-making process and how choices are affected by AI 18

6. The risk for the market trust 20

6.1. The anticompetitive aspect of dynamic pricing: personalised pricing 20

6.2. Competition policy approach to personalised pricing 22

6.3. Qualifying personalised pricing as an abuse 23

6.4. The OECD proposal of an enforcement framework 24

6.5. Possible measures to remedy 25

Introduction

The aim of the following paper is to illustrate the mechanics underlying a widespread pricing structure that is often overlooked: dynamic pricing. The diffusion of such a scheme is mainly attributable to the growth of e-commerce and, as a result, most of the processes that lie behind the application of this strategy are opaque.

In first place, an accurate definition of dynamic pricing will be provided, highlighting what makes it different from a static pricing strategy and providing examples of its effectiveness. Furthermore, the analysis will provide sufficient tools to understand when to apply this scheme, assessing the impact of several determinants on the success of the strategy.

In addition, a detailed breakdown on the roots of this strategy will be conducted: the background and the first applications, the development and the diffusion, the application in fields that could not be anticipated.

The study will then take into consideration the role of historical data, discussing the extent to which looking at past prices can be a viable option when setting prices. As it will be shown, reasons for the further diffusion of dynamic pricing is the development of technologies, based on algorithms run by artificial intelligence, that can prove to be a critical factor in enhancing the effectiveness of this strategy.

The second part of this paper will be devoted more specifically to the implications deriving from the diffusion of such a strategy. In detail, it will entail an analysis of the effects on consumer and producer surplus, that will give an explanation of the microeconomic consequences of the application of dynamic pricing. On the other hand, the legal and anticompetitive aspects of a branch of dynamic pricing, personalised pricing, will be discussed, emphasizing the position of the OECD (Organization for Economic Co-operation and Development) and its proposals for remedy.

1. What is dynamic pricing and why firms use it

Before trying to define dynamic pricing, it is useful to look at an example that Prof. Werner J. Reinartz used to tell his students. Assume it is a cloudy day with a 60% chance of rain, umbrella sellers will position themselves along the streets, offering umbrellas for 5 euros only. As long as it did not actually rain, demand for umbrellas was very low. Once it started raining, sellers increased prices up to 15 euros and simultaneously demand for the good increased steeply. This is a clear example of dynamic pricing. It consists of promptly changing the price at which a good or a service is offered according to changes in determinants that affect demand. This strategy has developed quickly in the last years, giving birth to several different applications that include the so-called personalised pricing, to which further attention is devoted in the following paragraphs.

As previously stated it could seem that any change in the price of a good is the result of the application of a dynamic pricing strategy, even if it is not necessarily the case. The narrower definition of this strategy states that an application of dynamic pricing occurs when the main variables that lead changes in prices are driven by variations in demand for that good/service, the time of purchase, competitors' prices and stock inventory. Furthermore, dynamic pricing allows to maximize revenues from sales, differently from changes in price that do not take advantage of algorithms to compute the extent to which prices should modify. Fluctuations in prices can take place with different timings: consequently to a change in determinants of demand, independently from the last price movement, after the achievement of predetermined target sales, or according to given time frames.

To apply this pricing structure, firms assume that they are facing rational, price-sensitive consumers.

1.1 Rational decision-making process

Rational decision-makers go through four main phases when deciding to purchase a good: need recognition, information search, evaluation of alternatives, and purchase decision.

Need recognition is the first step. The purchase process starts when the consumer realizes that she has a need that is sufficiently pressing to push her to seek satisfaction of it. It can arise from internal or external stimuluses.

Information search is a part of the process which does not always take place. Nonetheless, in this leg the consumer is expected to look for further information about the good she wants to purchase.

Evaluation of alternatives is the stage in which the consumer uses information at her disposal to narrow the field of alternative goods that can satisfy her need.

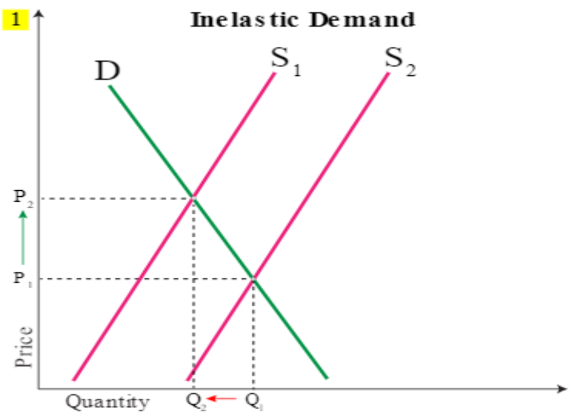
Purchase decision is the final step of the process. The consumer will buy the product that is coherent the most with the evaluation she has conducted up to this point. Between the purchase intention and the effective purchase, a crucial role is played by the evaluation of other factors, the most important of which is price. Price is the decisional incentive around which the whole dynamic pricing theory revolves around.

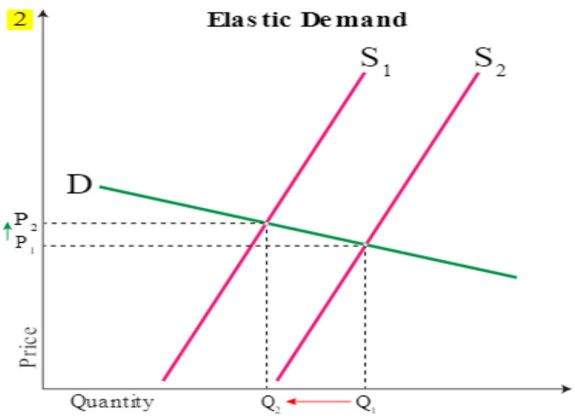
1.2 How elasticity affects the success of dynamic pricing

Price elasticity of demand is an economic measure that assesses the change in demand of a given good resulting from a change in the price of such product.

$$\text{Price Elasticity of Demand (PED)} = \frac{\%\ \text{change in Quantity Demanded}}{\%\ \text{change in Price}}$$

Determining whether consumers display a demand that is elastic or inelastic is crucial for any market participant. Moreover, it is fundamental for firms that decide to apply a dynamic pricing strategy. Consumers' demand of a good is said to be inelastic (1) if a percentage change in the price of the good causes a change in demand that is less than proportional. On the other hand, if the percentage change in price causes a more than proportional change in the demand of the product, demand is said to be elastic (2). PEDs > 1 in absolute value are associated with elastic demand, whereas PEDs < 1 are symptom of inelastic demand. The case in which PED= 1 is a very peculiar case in which a percentage change in price of the good causes a proportional change in demand. This scenario is called unit elastic demand.





Factors that influence price elasticity of demand are embedded in the characteristics of the product intended for sale and of the relevant market, though the two most relevant factors prove to be:

-) competition → more precisely the substitutes of the good sold. The more available substitutes in the market, the greater elasticity of demand for the product is going to be.

-) relevance of the good or service → goods that are strictly necessary, such as food and water, tend to be more price inelastic.

In light of those considerations, it is even more evident that before deciding to apply a dynamic pricing strategy, firms should be aware of the composition of the market in which it operates and of the behaviour of consumers in response to price changes.

To conclude, it is necessary for firms to investigate consumer preferences and market characteristics. If demand of the good offered turned out to be inelastic, changing price may not be an effective strategy to increase profits.

2. The industries where it is applied

The diffusion of dynamic pricing is a matter of the last decades, even if evidence of the first applications of this strategy can be dated back to the early 70s, in the airline industry. From that moment onwards the management of pricing schemes developed continuously, finding applications in more and more industries, with different intensities. Yet, proof that this strategy could be implemented years, if not centuries before, exists. In fact, despite the lack of dating, scalping is a procedure that had been applied for a long time. It consisted of the purchase of massive quantities of tickets for a given event, reselling them nearby the location of the contest, at prices that resulted to be dynamic, as they varied according to demand and the outcome of the single negotiations. This practice is now applied intensively in the online secondary market, where the role of algorithms, deeply illustrated in the following sections, is substituted by the risk propension of the resellers.

An effective application of the dynamic pricing strategy requires some market conditions without which the implementation of the model would not bring about concrete results:

-) perishability of the good/service offered → this condition has two significant consequences. The first one is that any amount not sold will have its intrinsic value written off. The second one is the availability of a limited quantity of the good in offer. This is the most relevant condition for those that operate in secondary markets.

-) possibility of anticipated sale → given this condition, sellers can vary the price as a consequence of the effective demand faced.

-) possibility of market segmentation → different willingness-to-pay allow firms to create dissimilar offers for diverse categories of customers, that display different price elasticity of demand.

-) predictability of demand → factors such as the quality of the teams involved in a football match allow for a more accurate forecast demand.

2.1 First application

The first evidence of the use of this model is attributed to American Airlines, between the 70s and the 80s after years of study and experimentations. The airline industry has always been characterized by low profitability margins, which has brought market participants to seek alternative ways to reduce costs and increase profits. The most evident result of this market analysis is the creation and diffusion of low-cost airline providers. In addition, firms, both low-cost and non, have devoted increasing attention to ancillary services. It allows to target several customer segments, offering lower base prices while aiming at earning higher margins via these additional amenities.

Before of the introduction of dynamic pricing implemented by American Airlines, airline companies used to charge consumers a single price for each route. The innovation brought about by the company included discounted fares for passengers that reserved early and higher costs for the reservation of specific seats, targeted for higher-tier customers. This basic revenue management tools proved to be very effective for the company: profits earned by the company increased by $500 million after the enforcement of this pricing strategy.

The airline industry has been the pioneer in the application of dynamic pricing, as the features of the market are consistent with the ones that have been previously listed. Moreover, the high fluctuation of the demand, which varies in time, within a matter of weeks, days, and at times hours, made this industry a very prolific field for the development of this strategy.

2.3 Development

As a consequence of the growing success of dynamic pricing in the airline industry, this model has started to be applied in more and more sectors. In particular, with reference to the entertainment scenario and ticketing. Nowadays, consumers are used to the idea that prices may vary when the service being purchased is associated with hospitality, transportations, or when buying tickets for a sports event. This has not always been the case, even if the introduction of such a pricing scheme has proved to be a profitable move for service providers quite consistently. In most cases an increasing performance of service providers has been associated with the possibility to reach a wider number of consumers, making even the latter better off. To illustrate the benefits of the strategy an example is provided.

In the history of American sport, San Francisco Giants is the first agent to apply a dynamic pricing mechanism in 2009. Thanks to the cooperation with an algorithm provider company, 2000 tickets, out of the more than 40000 tickets, turned from a static pricing structure to a dynamic one. The tickets opted for were usually not sold, for the largest part. This approach has allowed to take into considerations factors that were previously not considered, such as weather and the quality of the opposing team. Subsequently, the extraordinaire results of the strategy led to the application of the model to all the tickets in offer. As previously stated, financial performance improved considerably, increasing match-day revenues by 7%. Even consumers turned out to be rewarded, occupation of the seats in the stadium increased by 5%.

2.4 An unexpected application

On the contrary, consumers tend not to associate dynamic pricing policies to physical stores. Most of the online sellers base their offerings on algorithms that compute steadily the price at which to sell a product, targeting consumers with different willingness-to-pay. Goods sold in stores use to have a price label associated to it, making it difficult for sellers to change the price continuously. Surprisingly, the grocery industry has managed to apply dynamic prices to its products. The old-fashioned, fixed-price labels are now being replaced by the ESL, Electronic Shelfs Labels. Via this tool, retailers can finally compete with the e-commerce, that was slowly eroding the profits earned by physical markets. A new technology developed by Wasteless is able to track down trend of sales, inventory, and day of the week. This tool allows retailers to set dynamic prices on their products. Accordingly, goods that are closer to the expiry date are on a discount, whereas those further from it are offered at full price. The impact of this methodology on the industry is potentially outstanding: currently the retail market wastes 57 billion Dollars due to products spoiling.

Seeing an application of dynamic pricing in the world of the healthcare would be even more surprising. The introduction of this tariffs could allow for more accurate prices for appointments, basing on determinants such as historical data of demand of appointments in a given time band and availability of personnel. As a result of the structure of the dynamic pricing model, it is easier to imagine its application in private healthcare systems, such as the United States' one. Along with this restriction, the main issue that has prevented the arrival of dynamic pricing in this industry is that price works in a counter-intuitive way with respect to the industries taken into consideration up to this point. In fact, low prices are related strongly with low quality of the service provided. Thus, price is a weak tool to attract clients in this field. Despite it, experimentation is on due course and the introduction of dynamic pricing in the industry may be only a matter of time.

3. How it works

In the previous sections a brief intuition of how dynamic pricing works has been supplied, alongside the illustration of the industries where this strategy is applied. In the following chapter, the aim will be to provide insights on the mechanics that make this method effective.

First, firms should make a decision on the object of discrimination. Thus, if the strategy will be applied according to the type of good sold, basing on the profile of the client, or a mixture of both. Once it has been decided, it is necessary to identify the tool through which the procedure will be applied. This role is played by algorithms, that can be based on several determinants. Other than algorithms, firms could decide to implement a manual dynamic pricing strategy. Though it is the most common practice, it does not allow for high efficiency compared to algorithms, as it can not rely on highly complex, mathematical tools that instead characterize computer-based pricing decisions. The third and final step is to determine the frequency with which prices will vary.

As previously stated, there are many different algorithms that firms can decide to take advantage of. In particular, a detailed analysis of algorithms based on historical data will be conducted. Furthermore, hints on the functioning of more versions of these programmes will be given.

3.1 Historical data

A mention of the role played by inventory and expiry date on retail products has been already presented. These two drivers alone can be sufficient to implement a dynamic pricing strategy, as previously shown. Now consider the case in which there is the possibility of gathering historical data about the trend of sales of such a product. What if the previous sales cycles suggested that purchase of the good occurs even when getting closer to the expiry date? In this case, probably, the firm would not need to apply a discount and enjoy the benefits provided by a full price sale. Hence, it is possible to run dynamic pricing strategies with the use of algorithms relying on sales history.

The exploitation of such data brings about numerous benefits. In the first place, it allows to set very accurate prices, if the data at disposal are large in number and high in quality. In addition, firms can update consistently the system, managing to track down any change in the behaviour of their clients.

On the contrary, previous performance is not necessarily bound to continuity. This concept is widely acknowledged in financial markets and should be taken into consideration even in the goods market in which undertakings operate. The performance of bonds, for example, is so heavily influenced by exogenous variables, that the weight of historical data on prices is reduced. Whereas in markets where the purchase process of a product is more linear, even if influenced by several variables, it is possible to exploit the data available, with an appropriate amount of the latter.

3.2 Algorithms

Alongside the ability of the revenue management staff, the choice of an appropriate algorithm is crucial for the success of a dynamic pricing strategy. After having illustrated the potential of historical data in the application of this method, a deeper insight of algorithms based on such information is necessary.

The analysis of these data allows to profile the activity of consumers with respect to a product. Firms can gather this information in a number of ways:

-) via webservice → a web service is an application or data source that is accessible via a standard protocol. It is the most valuable option.

-) database sharing → it can be a worthy alternative to web service, but it is not always an applicable procedure as it involves trade of personal data of consumers.

-) via file or paper-based grids → these two options involve the highest degree of effort with the lowest outcome. Amount of information is constrained, and computational abilities are diminished.

As soon as historical data have been gathered, a dynamic pricing engine can be developed. In order to do it, three further elements need to be defined accurately. First of all, the mathematical model. It is a fundamental component of a dynamic pricing algorithm. In fact, it is the descriptor of the event. The final aim of a firm that applies this strategy is setting a relationship between historical sales and current prices. In order to do it, firms run regressions on historical series of data. Historical series are characterized by four main determinants: trend, seasonality, cyclic component, and the error. Trend refers to the essential component of the historical series. It entails the long-run tendency of the series. The cyclic component describes all the fluctuations around the trend. It is particularly relevant for firms, in fact it can be interpreted as the lifetime of a product within the market. Anticipating future positive/negative variations allows to the company to anticipate demand increase/decrease rates. Then, seasonality. It is the periodic component of the series. This determinant is usually quite consistent over the course of the years, in the sense that fluctuations occur in the same period and with the same intensity. The variables determining this component are numerous and very hard to predict. Firms should take into consideration this variable in their price-setting procedure and treat it as an exogenous variable. The impact of this component varies across industries. For instance, this variable has a great relevance in the determination of ticket airline prices. Christmas holidays and August are periods in which airline companies face a pick of demand, on the same note, November and February are, typically, periods of lower demand. The last component is the error. It entails all variations that can occur for which the previous components do not account for. Thus, firms will be faced with a price curve that shows all the previous combinations of price and demand and the price at which profits would have been maximized. Firms can then use this information to set current prices. Furthermore, during this process, firms should be able to identify the variables that influence the price, remove the ones that do not impact it, as well as eliminating redundant variables.

The determination of the mathematical model provides a solution to the second matter of contention: the forecasted outcome of the model. If the previous step has been performed properly, this stage should be relatively trivial. Envisaging more scenarios allows for higher efficiency; firms should be enabled to target the most favoured result with significant accuracy.

Eventually, the frequency with which prices will vary is to be determined. This topic does not have a common solution that applies for all the users of this method. The decision on this subject does not involve only profit maximization or quantity of products sold, it involves operational needs of the seller and technical constraints (more effective algorithms bring about higher costs for both implementation and maintenance).

Another relevant algorithm is the one based on the analysis of competitors. It allows to implement a dynamic pricing scheme that is not based on the product in offer itself, rather it focuses on prices charged by competitors on similar or substitute goods. The choice of this method depends severely on the type of market in which firms operate. Applying such a policy when selling a good that is identical to the one of competitors, for instance, may not be a successful strategy. If algorithms were instructed to change the price intercepting promptly any variation in prices charged by other companies, the former company would be applying a peculiar version of dynamic pricing, the so-called “reactive pricing”.

The last category of algorithms taken into consideration is based on the analysis of the potential customers. These mechanisms process information such as how many times a user looked for a given product on the internet, if it has looked for similar products in the past, up to analysing potential interests arising from her activity on social media. Profiling of clients in such a personal way defines the "personalised pricing" strategy, that is a widely debated topic nowadays, both for its ethical and legal implications. These considerations will be examined in depth later in the paper. With regard to the turnover of these algorithms, they can be highly effective as the different willingness-to-pay of consumers can be easily deducted. On the other hand, policies like this one are not able to exclude some false positives. A user could decide to buy an expensive laptop because she is particularly fond of information technology, it does not imply that she is price-insensitive in other sectors as well.

4. Industry vs. Customers

The analysis that has been conducted up to this point has always taken into consideration the perspective of the firm. Firms can maximize their profits by using appropriate dynamic pricing strategies. Different strategies can be applied consistently with the characteristics of the market and of the clientele. Intuition suggests that the application of dynamic pricing may be a zero-sum game. On the contrary, dynamic pricing policies can represent a win-win solution, as both firms and consumers can benefit from it. A well-designed strategy is consumer-friendly. Consumers should be aware of how the system works and should be empowered to make a conscious choice. Granting this condition allows firms to generate more profits as they can sell to more consumers at prices which correspond to their maximum willingness-to-pay, and it makes the product accessible to a wider range of users, making even the latter better off. As previously mentioned, the threats for consumers arise when firms implement a more aggressive approach to dynamic price discrimination. Personalised pricing exploits differences among consumers at the major benefit of the firm itself.

4.1 **Customers' point of view**

Paying different prices for the same good is something that may be misleading. In fact, not all consumers have accepted the introduction of dynamic tariffs. Even if the development of this strategy is certainly aimed, in the first place, at increasing firms' profits, it does not imply that consumers can not benefit from it.

Disney, Uber, and others that are implementing dynamic pricing strategies, typically have a fixed capacity to serve customers and (after a certain threshold) have to turn customers away. By increasing or decreasing prices basing on demand, firms are letting the most profitable customers self-select, while simultaneously encouraging others to come at a different time.

This is where the misconception takes place. Consumers perceive increased rates differently than discounts. Thus, users think they are being cheated instead of being incentivized. For some business that have tried dynamic pricing the customer backlash has forced them to abandon the practice. Despite it, consumers' consensus to this strategy is increasing, as more and more users managed to recognize the benefits offered to them.

What can be effectively harmful to consumers is the application of personalised pricing procedures. In this scenario consumers are potentially worse off. Users tend to associate dynamic pricing to personalised pricing in an incorrect manner. The two strategies are definitely bound, as mentioned personalised pricing is a development of dynamic pricing, but the welfare effects of the strategies are different.

4.2 How consumers can exploit it

A person browsing airfare rates from an apartment in Brooklyn early in the morning will most likely not see the same deals on the screen as someone browsing from a house in Buenos Aires late at night. Pricing is typically based on factors like location, time of day, time of week and overall customer demand. While consumers can not affect the overall demand for a product, they can exploit and circumvent the other elements that characterize dynamic pricing strategies.

Websites that use this pricing procedure collect and analyse data about every visitor to predict what a customer is willing to pay. Prices are then adjusted automatically for each individual visitor, via the algorithms previously illustrated. Getting the best available offer is a man versus machine case. How can consumers outsmart dynamic pricing?

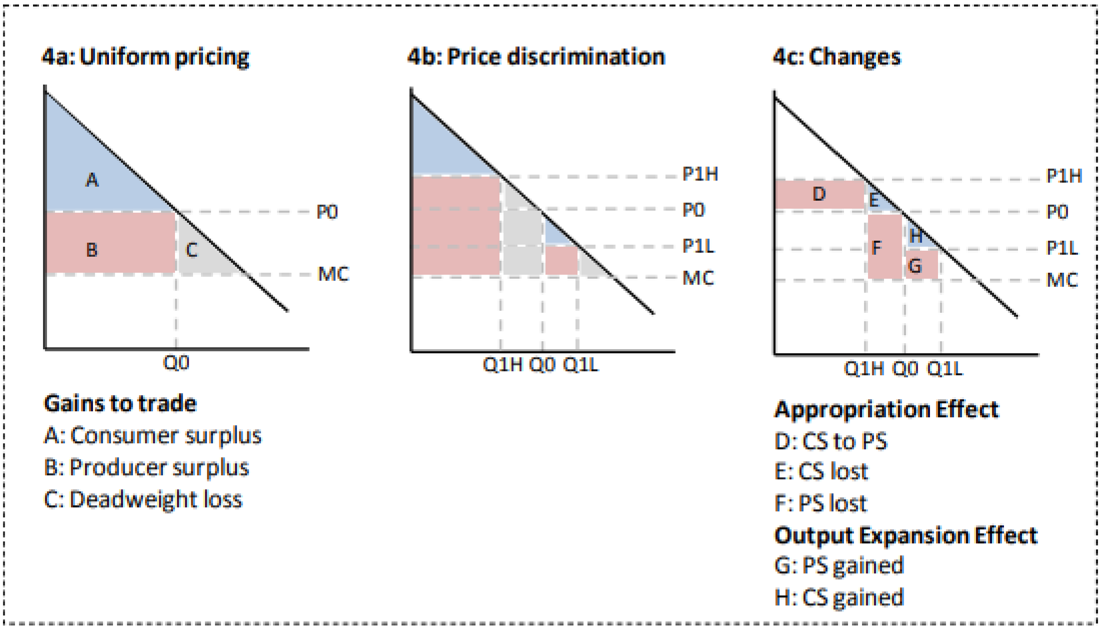
The first step to take when trying to "beat the system" is making sure that the company in question adopts a dynamic pricing strategy. Visiting the same website from different mobile phones and laptops will give out different prices if it is the case. Devices associated with different owners are linked with different willingness-to-pay, thus prices will be dissimilar.

The key to exploitation of dynamic pricing strategy is appearing to be a new customer. Firms usually present to new customers lower prices in order to acquire them as clients. Then as the number of purchases and the number of information on the individual increase, prices will go up according to the profile in examination. The secret to hacking dynamic pricing is essentially hiding any trace of your browsing history or personal details before a website's bots can see them. Users can download a new browser and use it to purchase the product they wanted or use the incognito mode so that their personal information are hidden.

4.3 A microeconomic consideration: the extraction of surplus

To assess the microeconomic consequences of such policies of price discrimination, it will be useful to begin the analysis from a generic monopoly situation. Starting from this assumption is reasonable as any firm that applies a dynamic pricing strategy is supposed to have some market power. Under uniform pricing the benefits resulting from trade are shared between producer and consumers. This first scenario is represented by the leftmost graph in the figure below. Then, if the monopolist is able to price discriminate, it will set different prices for different categories of consumers. A graphical representation of what happens in the market is provided by the central graph. Via price discrimination the monopolist identifies groups of consumers with higher willingness-to-pay and charges them higher prices, thereby appropriating of some of their consumer surplus. This is the so-called “Appropriation effect”. That is, some of consumer surplus (A in the graph) is converted into producer surplus. However, price discrimination also allows some consumers (represented by the segment Q0-Q1L in the graph) that previously could not purchase the product, to buy it.

The overall outcome on the market is shown by the last picture. The effect on consumer surplus is ambiguous. In concrete applications of the model it depends on the degree of price discrimination: dynamic pricing in its broader application will likely benefit consumers, as well as producers, whereas personalised pricing is expected to damage consumers, further increasing producer surplus. To conclude, price discrimination may increase social surplus as it decreases in most cases deadweight loss.



5. Big Data and AI

The term big data is relatively new, even if the underlying concept of colleting large amount of information for analysis purpose is aged. Big data has been defined in several ways by different authors. For the purpose of this paper, the definition adopted is the one proposed by industry analyst Doug Laney in the early 2000s. Nonetheless, this definition is the more widely accepted one. Big data are characterized by the 3 Vs: volume of data, variety of data, and velocity. Over time three more Vs have been added in order to give a deeper understanding of big data. They are veracity, value and variability. The first three concepts are more intuitive: big data are such if the volume of data is extremely large, there is a wide variety in the data collected, and the velocity at which this information is generated, gathered and processed is considerable. Data veracity refers to the quality of data. Uncertain data sets can cause serious issues which are difficult to address. Bad data leads to inaccurate analysis and may undermine the value of business analytics because it can cause executives to mistrust data as a whole. Data value refers to the relevance of information gathered for the company. Collection of data that display no real value to the company can harm the validity of the whole process. Variability allude to the width of data collected, the ways in which information can be processed and formatted.

5.1 Clients' profiling and the Uber case

Computers have long been used to collect sales data, organize customer lists, and identify market segments. The diffusion of the use of big data for commercial purposes is attributable to two main trends. The first one is the increasing adoption of information technology platforms. It is sufficient to consider how relevant the Internet and smartphones are in everybody's lives to have a good indicator of such event. These tools give the users access to numerous applications such as maps, search engines, music services, and a variety more. Access to these applications, however, is not granted only to users. In fact, these data can now be tracked down, allowing businesses to know one's position, browser history, and musical likings. Most of this data collection occurs via cookies that website's owners place on the webpage. Accepting these cookies allows the site to store information about the interaction of the user with the website. In the long-run, cookies contribute heavily to the determination of the profile of a consumer. The second reason why big data analysis is more and more relevant in today's market is the widespread increasing trend of the ad-supported business model, and the creation of a secondary market for information. Companies such as Google and Facebook can track down several, sensible information of their users. It gives those companies (and many others that operate in analogous ways) two profit opportunities: resale of information and sale of targeted marketing opportunities. The former consists of mere resale of personal information. This business is growing quickly as market participants recognize the potential of targeting precisely their customers. On the other hand, instead of selling information directly, these companies furnish a service of targeted marketing. That is, advertisements are aimed at a precise group of consumers which can be accurately targeted with the information at disposal. Mass advertising involves revealing the same information to all consumers. Targeted advertising involves revealing different information to different subsets of consumers. This has fostered a growing industry of data sellers and information intermediaries that buy and sell customer lists and other data used by marketers to assemble a digital profile of individual consumers.

Market participants typically do not want to share with their customers that they take advantage of such data, so finding evidence of their exploitation is complicated. Nonetheless, it can be useful to mention the Uber case. The American company has been implementing a strategy that fits the features of personalised pricing. Further explanations on the dynamics of this pricing strategy will be provided later in the paper, at the moment this example can help explain how firms dispose of personal information. The company has been reportedly charging different fares to different consumers, basing on determinants that go beyond the simple conditions of traffic or time of the day. Customers that commuted from or towards a wealthy zone were charged higher price as a result of higher alleged willingness-to-pay. The extent to which the firm manipulates personal information is still unclear. Several users assert that fares changed when switching from personal to corporate credit cards. Furthermore, it has been postulated that variables such as battery level of the phone through which the run is being reserved and phone brand play a distinct role in the determination of the price. This example is only one of the available many that proves how vulnerable the single consumer is in relation to the firm.

5.2 How choices are affected by AI

Previously it has been assumed that consumers follow a rational decision-making process pattern when deciding to purchase a good. Even if this assumption is rather simplistic and points could be raised regarding the actual rationality of the average consumer, in this section a further step is going to be taken towards a more extreme consideration. The choices users make are effectively so? That is, do consumers choose what to buy?

The involvement of artificial intelligence and big data in people’s life is extended to almost every field. AI makes decisions for people in any of these areas without conscious involvement.

Machines track past patterns and those of allegedly similar people across the world, and then decide not just what news articles one should see, but with whom she should commune and forge bonds, what goods and services she should purchase. This influences opinions, relationships, purchases, and the overall society.

There are countless examples of how choices are induced by AI. When a consumer purchases a good on the web, she can enjoy the advantages of buying it comfortably for her own house. Apparently, the buyer is faced with billions of offers, but more often the products shown are related with recent searches and purchases. Another clear example is provided by Netflix. Once a user watches a comedy, or a thriller, or any genre of a movie, she will be continuously provided with more and more of the same kind of film. The narrowing effect of clustering groups of consumers is certainly effective from the firm's point of view, on the other hand it has a growth-limiting effect on consumers as preferences are based on past behaviour.

In practice, consumers are steady in their own characteristics. Range of exposure to alternatives, thus real, conscious possibility choices is narrowed by the presence of AI.

6. The Risk for the Market Trust

So far, the analysis has focused on dynamic pricing, providing only smaller insights on the strategy of personalised pricing. The purpose of the following section will be to state the fairness of such a practice, after having provided a more accurate definition. In order to do it, this study will indicate how competition law is defined and what practices are considered illegal by the antitrust forces. Then, personalised pricing will be contextualized in this framework, underlining the anticompetitive aspects of this strategy and the possible remedies to its exploitation.

The increasing diffusion of pricing algorithms and the growing use of big data analysts by companies, has raised concerns about the possibility that undertakings engage in strategies of personalised pricing discrimination. As previously illustrated, the effect of this strategy is potentially harmful for consumers. Even if some categories of users may be better off, as the product may be more accessible, the overall consumer welfare decreases in most occasions. In addition, the implementation of this policy in non-transparent or deceptive means risks diminishing market trust, creating a widespread feeling of unfairness, as consumers pay different prices for the same product with no apparent reason. In the long run, it can further decrease consumer welfare and reduce consumer market participation.

A particularly significant position on the issue is the one held by the OECD. The organisation is one of the most relevant authorities in the field of economic co-operation between its member states. It proposes guidelines and best practices to which governments align themselves, spontaneously. In November 2018, the OECD commission faced for the first time the theme of personalised pricing. During the course of this meeting, the commission discussed the ambiguous effects of personalised pricing. Specifically, if the strategy required a policy intervention and, if so, what are the appropriate tools to address it.

6.1 The anticompetitive aspect of dynamic pricing: personal pricing

These two forms of pricing are frequently confused, at times they are used even as synonyms, even if it is not the case. Dynamic pricing is based on changing prices continuously during the course of a certain period of time. The determinants driving these variations are not customer-related. Changes in demand, time of the day, the volume of traffic on the product's webpage lead to price movements. Moreover, users belonging to the same clusters will be shown the same prices.

On the other hand, personalised pricing is a practice of price discrimination that is based on customers' personal characteristics and conduct. Therefore, price set for a good becomes an increasing function of a customer's willingness-to-pay. This practice is particularly common in digital markets, where the amount of data collected online by firms allows them to track down consumers' profile. After having provided a definition of personalised pricing, it is useful to understand how firms can implement this strategy. Three main steps are required. First, data collection. It can occur in three further manners:

1) data provided voluntarily by consumers. An instance is the case when individuals fill an online form.

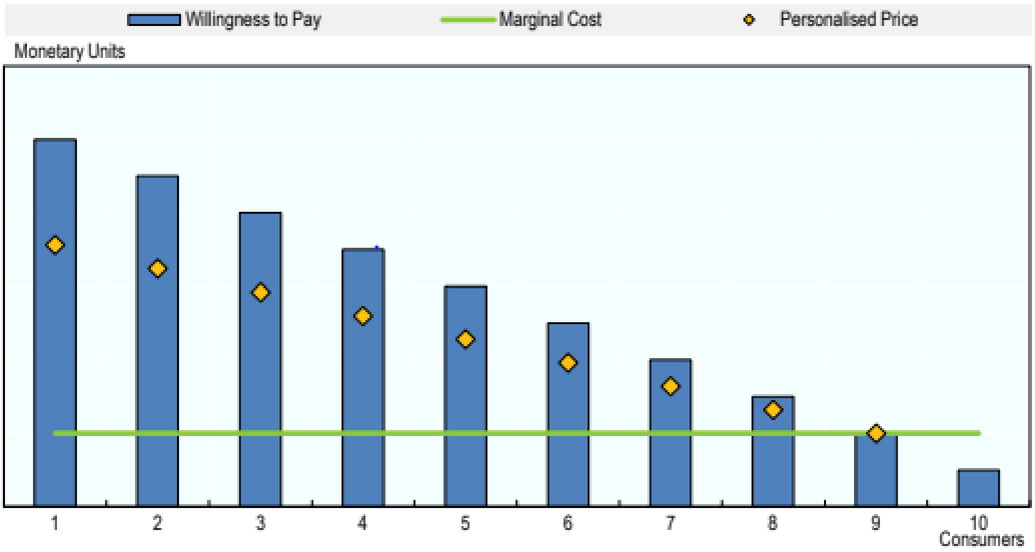
2) data directly observed by the company. The use of cookies by firms falls in this category.

3) data inferred from consumer behaviour. This type of data collection is very resource-consuming for undertakings as it uses advanced data analytics.

Volunteered data	Observed data	Inferred data
Name	IP address	Income
Phone number	Operating system	Health status
Email address	Past purchases	Risk profile
Date of birth	Website visits	Responsiveness to ads
Address for delivery	Speed of click through	Consumer loyalty
Responses to surveys	User's location	Political ideology
Professional occupation	Search history	Behavioural bias
Level of education	"Likes" in social networks	Hobbies

The second step is estimating customers' willingness to pay. This variable is not observable from the data companies have at their disposal. What companies do with the information they own is implementing advanced regression models that create a relationship between personal characteristics and willingness-to-pay.

Lastly, basing on data previously collected and on the estimation of customers' spending capacity, firms must set the optimal price for each consumer. Though it is often assessed that firms charge each consumer the full value of her willingness-to-pay, it is not necessarily true. In first place, undertakings are aware that the willingness-to-pay computed for each consumer is no more than an estimation, that can be wrong by definition. In addition, there may be some level of competition that prevents firms from charging too high prices. An insight of the prices charged by firms applying this pricing strategy is provided by the figure below (the graph shows on the x-axis different consumers, and on the y-axis the price charged to each of them).



In conclusion, both types of pricing require a large degree of sophistication and fall in the macro-category of price discrimination. The main difference is that discrimination is customer-centric in the case of personalised pricing, whereas in dynamic pricing it is not.

6.2 Competition policy approach to personalised pricing

The potential risks of personalised pricing can be addressed through competition law. As far as competition policy is concerned, personalised pricing can potentially be defined as an abuse of dominant position, since it can force consumers to pay higher prices than they normally would, thus decreasing consumer welfare. In order to understand if and how competition policy can qualify the implementation of dynamic pricing as an abuse of dominance, a digression on the current law and regulations on the topic is necessary.

Abuse of dominance is prohibited by Article 102 of the Treaty of Functioning of the European Union. A conduct by a firm is qualified as such if the company engages in activities aimed at increasing or maintaining the position it holds in the market. Behaviours that characterize an infringement of this article are distinguished in two categories: exclusionary and exploitative conduct.

The former consists of actions undertaken by the company to harm competitors or to exclude them from the market. Consumers in this case would see breadth of choice decrease, while the firm could set higher prices, or decrease quality of the product offered, due to the lack of alternative goods.

Exploitative abuses instead harm customers directly, differently from the previous case. Instances of this conduct can be excessive pricing and price discrimination.

Nonetheless, some conditions need to be met by a firm to determine the anti-competitiveness of the conduct of a firm:

1) the offender must hold a relevant position in the market. That is, the firm needs to have market power.

2) the conduct must fall in one of the categories of infringements previously mentioned. This condition states that holding a dominant position is not unlawful per se, abuse of the position causes an infringement of the law.

3) the conduct must display concrete negative effects. Actions that do not harm the competitiveness of the market, or conducts whose effects are counter-balanced by efficiency are not punishable.

Some competition authorities have opened files and investigation to challenge the abuse of personalized pricing, using the tools mentioned above. To date, there is no case law in the field of dynamic pricing. That is, no infringement of competition has been established by the law yet.

6.3 Qualifying personalised pricing as an abuse

Whether the application of a personalised pricing strategy can be considered an abuse of dominant position is a largely unsolved question. As far as abuse of dominant position is concerned, antitrust authorities should determine an infringement that falls in the cases provided for by the law. Furthermore, the lack of case law on price discrimination policies makes the task even more complex.

Notwithstanding the difficulty of assessing the abuse of dominant position and the lack of case law in this field, there is an argument to be made with regard to the possibility of treating personalised pricing procedures as exploitative abuses. In this sense, it would be necessary to prove that the rationale for which consumers pay different prices is not bound to costs, and, more importantly, that personalised pricing is a form of excessive or unfair pricing. Given that, antitrust authorities could intervene in defence of consumers.

In addition, personalised pricing could be treated as exploitative abuse, in some cases. Specifically, whenever a firm that holds a dominant position decides to cut prices offered to rivals' customers, in attempt to hamper competition in the market. However, this approach entails more the mechanics of predatory pricing rather than the exploitation of consumers arising from personalised pricing.

In conclusion, it seems possible to address the implications caused by personalised pricing via competition law. On the other hand, antitrust policy has also some limitations. In fact, up to this point, personalised pricing has been treated as an abuse of dominant position, but not all the firms that apply this strategy can be defined as dominant in their respective markets. Nonetheless, the negative consequences brought about by personalised pricing are definitely more severe when the strategy is applied by larger firms.

6.4 The OECD proposal of an enforcement framework

To date, there is no framework that provides competition authorities with guidelines to cope with an alleged abuse resulting from the exploitation of personalised pricing strategies. The following may be a viable model in order to assess such infringement. The foundation of the proposal promoted by the OECD is based on five points.

1) Identify price differences not based on costs. The differences across prices that consumers face need to be a consequence of discriminatory pricing. If price discrepancies result from different marginal costs faced by the firm in serving different cluster of customers, there is no abuse of exploitative practices, nor an infringement of competition law.

2) Establish dominance. Verifying that a firm holds a dominant position in the market is necessary for the application of laws in this area. Furthermore, the more severe consequences of personalised pricing are caused by firms holding market power. Evidence of the use of this strategy has been found even in more competitive markets, so competition authorities can not overlook this step.

3) Analyse effects on consumer welfare and efficiency. As it has been stated before, welfare effects of personalised pricing are ambiguous. Policy makers should consider total welfare, not only consumer welfare.

4) Assess the persistency of the effects. The implementation of this strategy does not necessarily deserve an intervention if the results it brings about for consumers and competition are not persistent. If the market displays characteristics such as barriers to entry, high switching costs or low level of competition, a mediation of the competition authorities may be required.

5) Identify the source of discrimination. Determining which are the factors on which discrimination occurs may help to determine the appropriate measures to remedy.

To summarize, if a personalised pricing strategy is adopted by a firm whose market power is significant, and the effects on the competitive landscape are negative and persistent, the competition authorities should intervene.

6.5 Possible measures to remedy

Competition authorities need to be able to evaluate and assess any abuse linked to the exploitation of personalised pricing. The framework formerly provided is only one of the tools that are being studied in order to cope with this phenomenon. On the other hand, institutions should also be able to prevent such abuse from occurring. One extreme option could be prohibiting personalised pricing completely. Even if the problem would be apparently solved, this may be not be the most efficient solution.

One first option could be requiring firms to tell consumers that they use a personalised pricing strategy. Firms could involve consumers in the insights of their strategy, telling them how the price was calculated. As well as that, firms could ask consumers' consensus to use their personal data to customize prices. Further proposals include giving the customer the choice to take part into the dynamics of personalised pricing or not. In this scenario, customers would be provided with a price list including both personalised and non-personalised price.

These remedies would reduce the risks associated to personalised pricing, giving consumers control over the disposal of their personal data. Additionally, users would be keener on accepting such pricing strategies as a result of the increasing transparency, contributing to restore market trust.

Competition law is one of the ways in which personalised pricing can be dealt with. Another valuable tool is offered by consumer protection law. The main difference between these two institutions is the focus on the market they have. Competition law focuses mostly on business-to-business interactions whereas consumer protection law targets business-to-consumer relationships. It allows authorities in the field to enjoy of a privileged position when considering the effects of personalised pricing on consumers.

Finally, privacy and data protection laws can provide powerful tools to undermine the exploitation of personal data by firms. Although the focus of this framework is not associated with business pricing decisions, practices such as collection and processing of personal data is definitely under the control of this authority. Privacy laws in most countries demands the exposure of the reasons of data collecting and processing. The use of this data for personalised pricing purposes would be disclosed, allowing for higher transparency and, once again, restored.

Reference List

- Competition and Markets Authority, Pricing Algorithms, CMA94 (2018)
- Office of Fair Trading, The Economics of Online Personalised Pricing, OFT1488 (2013)
- Executive Office of the President of the United States, Big Data and Differential Pricing (2015)
- Organisation for Economic Co-operation and Development, Personalised Pricing in the Digital Era, DAF/COMP (2018)13
- Massimo Dell'Erba – Federico Quarato, Dynamic Pricing, ed. Franco Angeli (2018)
- Hal R. Varian, Intermediate Microeconomics, ed. Norton, 8th edition (2010)
- Stacey Peterson, Effective Data Management to Combat the Coming Data Apocalypse (2019)
- Mark Nitzberg – Olaf Groth – Mark Esposito, AI Isn't Just Compromising Our Privacy- It Can Limit Our Choices, Too (2017)
- Web Service, Definition from https://techterms.com/definition/web_service, The Tech Terms Dictionary (2017)
- How to Outsmart Dynamic Pricing to Get the Best Travel Deals https://www.get.com/blog/how-outsmart-dynamic-pricing-get-best-travel-deals/
- OECD https://www.oecd.org
- Retail Systems Research, Dynamic vs. Personalised Pricing, https://www.rsrresearch.com/research/dynamic-vs-personalized-pricing (2017)
- American Airlines Dynamic Pricing, https://patentdebate.com/american-airlines-dynamic-pricing (2018)